Predictive Control of Wind Turbines by Considering Wind Speed Forecasting Techniques

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Abstract- **Fixed speed wind turbines have low efficiency as compared to variable-speed, fixed-pitch wind turbines. The latter are required to optimize power output performance without the aerodynamic controls. A wind turbine system is operated such that the points of wind rotor curve and electrical generator curve coincide. In order to obtain maximum power output of a wind turbine generator system, it is necessary to drive the wind rotor at an optimal rotor speed for a particular wind speed. A Maximum Power Point Tracking (MPPT) controller is used for this purpose. In fixed-pitch variable-speed wind turbines, wind-rotor parameters are fixed and the restoring torque of the generator needs to be adjusted to maintain optimum rotor speed at a particular wind speed for optimum power output. In turbulent wind environment, control of variable-speed fixed-pitch wind turbine systems to continuously operate at the maximum power points becomes difficult due to fluctuation of wind speeds. Therefore, a special emphasis is given to operating at maximum aerodynamic power points of the wind rotor. In this study, wind speed forecasting techniques are considered for predictive optimum control system of wind turbines to reduce response time of the MPPT controller.**

Index Terms-- **Maximum power point, Predictive control, Wind speed forecasting, and Wind turbine**

I. INTRODUCTION

Wind speeds continuously varies and although wind rotor is required to drive at an optimal rotor speed for a particular wind speed, wind rotor speed can not be instantaneously changed. Therefore, the response of the wind rotor to wind speed variation affects the performance of the system. Wind speed time-series data typically exhibit autocorrelation, which can be defined as the degree of dependence on preceding values[1]. Autocorrelated time series models are usually used for wind speed prediction. In an autocorrelated wind speed-time series, the value of wind speed in any one time step is strongly influenced by the values in previous time steps. Therefore, in this study wind speed prediction techniques are applied to improve the response of wind rotor speed variation and energy capture.

For optimum operation of wind turbines, if the wind speed is varied from V_1 to V_2, the wind rotor rotational speed should be changed from ω_1 to ω_2, as shown in Figure 1. In systems that employ wind speed sensors, the wind sensor provides the turbine rotational speed reference to the MPPT controller according to the wind rotor characteristics. This reference is compared with the actual rotational speed of the rotor. Wind speed, turbine rotational speed and wind rotor & generator characteristics are the main factors that determine the optimum operating points. Rotational speed of the system cannot be instantly varied due to the wind rotor momentum of inertia. Therefore, it is difficult to track optimal rotational speeds with wind speed variations. Response time of the controller depends on the turbulence dynamics and affects the performance of the system.

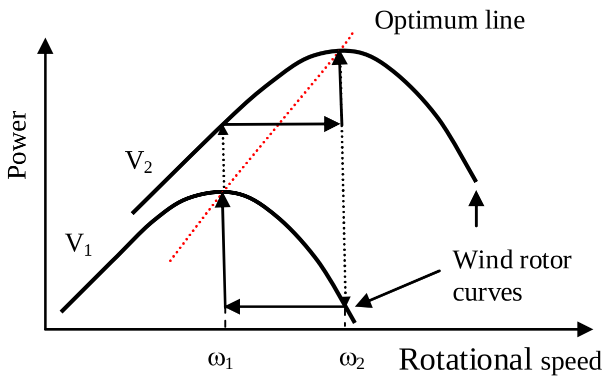


Fig. 1. Function of MPPT mechanism of a wind energy conversion system

II. WIND SPEED FORECASTING

Time series prediction takes an existing series of data and forecasts the future values. Linear statistical models are commonly used for time series prediction [2, 3]. The use of Neural-networks is also a promising technology in forecasting and can be used to predict time series wind data [4-9]. Neural networks can be classified into dynamic and static categories. Static (feed-forward) networks have no feedback elements and contain no delays; the output is calculated directly from the input through feed-forward connections. In dynamic networks, the output depends not only on the current input to the network, but also on the previous inputs, outputs, or states of the network. Dynamic networks can also be divided into two categories: those that have only feed-forward connections, and those that have feedback, or recurrent connections. Dynamic neural network method is more suitable for time series forecasting as it can be trained to learn sequential or time-varying pattern [10, 11]. For this study, a neural network incorporated with a tapped delay line with delay from 1 to 5 and five neurons in hidden layer is used for wind speed prediction. This is a straight forward dynamic network, which consist of a feed-forward network trained by back-propagation with tapped delay line at an input. This is part of a dynamic network, called focused networks, in which the dynamics appear only at the input layer of a static multilayer feed-forward network[11]. This is called the Focused Time-Delay Neural Network (FTDNN). Levenberg-Marquardt algorithm was used to train this network[12]. Network architecture is shown in Figure 2. The characteristics of the neural network used in this study are the followings;

Number of Input Delays: 5
Number of hidden layer: 1
Number of neurons in hidden layer: 5
Number of iterations for training: 100

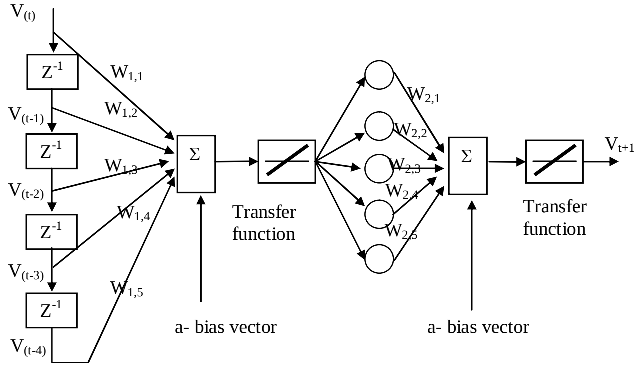


Fig. 2. The structure of focused time-delay neural network

III. SYSTEM SIMULATION

MATLAB neural network toolbox was used to simulate the focused time-delay neural network and trained incrementally. Measured wind data with 10 s sample time in the constricted site at Ekala, Sri Lanka was used to investigate the effective of neural networks for wind speed forecasting in turbulent wind condition. Dynamic neural network method was used to predict 10 second ahead wind speed value. Predicted and measured wind data are presented in Figure 3.
In order to measure the accuracy of prediction, the root mean square error (RMSE) was used.

$$\text{Root mean square error (RMSE)} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(v_i - v_{ip}\right)^2} \qquad (1)$$

$$=0.6768$$

where n is the total number of data points (135), v_i, are actual values of wind speeds, v_{ip} are the predicted values for v_i.

According to these results, focused time-delay neural network method is suitable for one time step ahead wind speed predictions. Zhang et al [10] have described that Neural Networks (NNs) perform better than linear statistical models, when the data is highly variable. It is not expected that NNs do better than linear models for linear relationship [13]. NNs are superior than linear statistical models, when wind speeds are predicted at a turbulent wind site where many disturbances exist. Normally, small wind turbines are installed in more constricted places, where the wind speeds are more turbulent. However, the computational complexity of linear statistical models is better than that of neural network[5]. Most important thing is NNs are independent of any mathematical model and adapt themselves to any kind of data set [14].

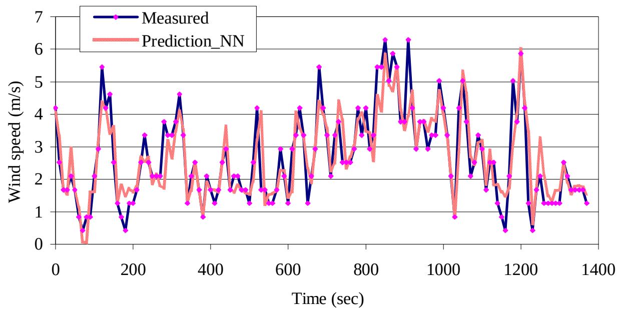


Fig. 3. NN predicted and measured wind data at Ekala, Sri Lanka

IV. PREDICTIVE CONTROL OF WIND TURBINES

A. Response time of MPPT mechanism

Response time of the controller depends on the turbulence dynamics and this effects to performance of the system[2]. This study is intended to reduce response time of the MPPT controller by defining constrains by wind speed forecasting. For quick response to speed variation of the wind rotor, maintaining a maximum possible rate of change of wind rotor rotational speed is important. The restoring torque of a generator is controllable.

When wind speed is changed, variation of rotational speed of the system can be derived as follows;

$$\frac{d\omega}{dt} = \frac{kT_a(v,\omega) - T_e(I_G) - T_f(\omega)}{J} \qquad (2)$$

Where

ω-Rotational speed, v-wind speed, J– Momentum of inertia of all rotating parts, $T_a(v,\omega)$- Aerodynamic torque by wind rotor side, $T_e(I_G)$-Restoring torque of generator (controllable variable), $T_f(\omega)$-Torque due to friction losses of generator & gear box (function of rotational speed), k-Speed ratio of the gear box.

Therefore, ideal response time of MPPT controller is;

$$t = \int_0^T dt = \int_{\omega_1}^{\omega_2} \frac{J}{kT_a(v,\omega) - T_e(I_G) - T_f(\omega)} d\omega \qquad (3)$$

B. *Improved controller with wind speed prediction*

In this study, ideal control criteria were considered to achieve optimum aerodynamic performance of the wind rotor (optimum tip-speed ratio). Predicted wind speed was used to control the rotational speed of the wind rotor. Control criteria are described in Table I and control diagram of the system is presented in the Figure 5.

Based on the wind turbine aerodynamic behaviour, the turbine catches only a part of the kinetic energy contained in the wind[15]; that is:

$$P_a = \frac{1}{2}.\rho.\pi.R_r^{\ 2}.v^3.C_p \qquad (4)$$

where P_a is the captured power by the rotor, R_r is the radius of the rotor (R_r =1.105m for this study), ρ is the air density and v is the speed of the incident wind.

The proportion of the useful power is defined by the power coefficient C_p, which depends on the tip speed ratio (λ).

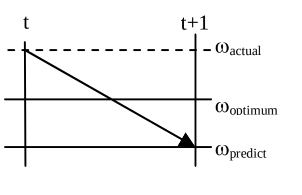
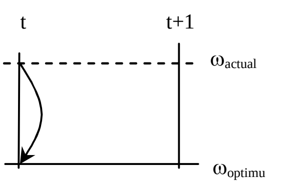
The rotor aerodynamic characteristics are represented by the C_p - λ relationship. Wind-rotor characteristics (shown in Figure 4) were used for this simulation study. Momentum of inertia of the system is 9.77kg.m^2 and optimum tip-speed ratio of the wind rotor is 6.3.

Using equation (4), the aerodynamic torque (T_a) of a wind rotor can be obtained as follows:

$$T_a = \frac{1}{2}.\rho.\pi.R_r^{\ 3}.v^2.\frac{C_p}{\lambda} \quad \text{where } \lambda = \frac{\omega.R_r}{v} \qquad (5)$$

TABLE I

CONTROL CRITERIA

With wind speed prediction techniques	**Without wind speed prediction techniques**
	
Control criteria: $d\omega/dt$ **is adjusted to achieve predicted optimum value** $\delta\omega = \omega_{predicted} - \omega_{actual}$	Control criteria: $d\omega/dt$ **is adjusted to achieve measured optimum value** $\delta\omega = \omega_{optimum} - \omega_{actual}$

Performance of the predictive controller was compared with a conventional controller which is operated without predictor. These two systems were simulated (in MATLAB) by considering ideal control criteria to obtain optimum aerodynamic performances of the wind rotor. In this study, the maximum reinstated power by the generator is 500W which is typical for small scale wind turbines. Comparison performances are shown in Figure 6. Summary of energy extraction for 1350 s period is given in the Table II.

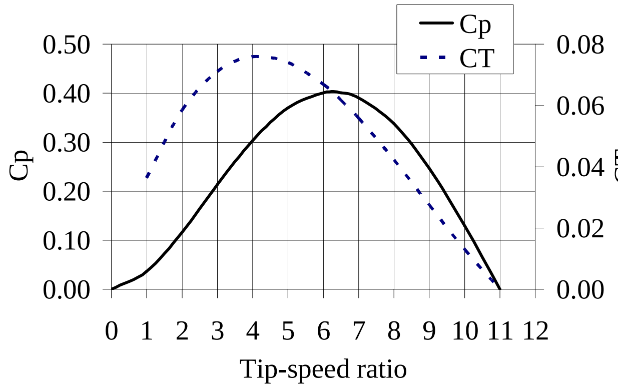


Fig. 4. Wind rotor characteristics

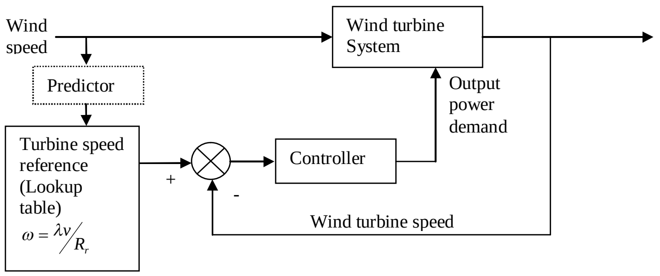


Fig. 5. Predictive control schemer with wind speed prediction

TABLE II

ENERGY EXTRACTION

	With wind speed prediction	**Without wind speed prediction**
Available energy	44.0218kJ	44.0218kJ
Extracted energy	34.9705kJ	32.9018kJ
Actual energy extraction %	79.43%	74.73%

$$\text{Available energy} = 0.5 \times A \times \rho \times C_{p\,\max} \times v^3$$

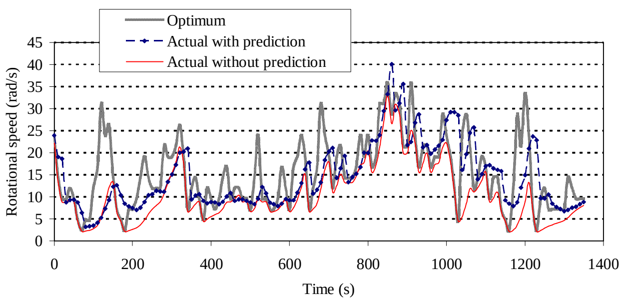


Fig. 6. Comparison performance

V. RESULTS AND DISCUSSION

This paper presents a comparison study of predictive MPPT control by using wind speed forecasting. Control criteria were developed by considering only rotor performance and simulations were performed with ideal MPPT control criteria for measured wind data. Performance of the predictive MPPT control was compared with conventional MPPT control system, which operates without predictor. The results obtained show that predictive control system improves the response time of the MPPT controller. The predictive controller performs well in turbulent wind condition and optimises the control loop in real time. The proposed controller provides a good means to maximize the energy capture.

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